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How to Decide the Best Fuzzy Model in ANFIS

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ABSTRACT : *Geoid height determination is one of the major problems of geodesy because usage of satellite techniques in geodesy isgetting increasing. Geoid heights can be determined using different methods according to the available data. Soft computing methods such as Fuzzy logic and neural networks became so popular that they are used to solve many engineering problems. Fuzzy logic theory and later developments in uncertainty assessment have enabled us to develop more precise models for our requirements. In this study, How to construct the best fuzzy model is examined. For this purpose, three different data sets were taken and two different kinds (two inpust one output and three inputs one output) fuzzy model were formed for the calculation of geoid heights in Istanbul (Turkey). The Fuzzy models results of these were compared with geoid heights obtained by GPS/levelling methods. The fuzzy approximation models were tested on the test points.*

KEYWORDS *-Adaptive Network Based Fuzzy Inference Systems (ANFIS), Most suitable number of subsets, fuzzy logic, input-output systems,geoid height*

I. INTRODUCTION

The geoid is an equipotential (level) surface of the earth's gravity field which coincides with mean sea level (MSL) in the open oceans. Geoid is very important for defining height because it provides a meaningful reference frame for it. The importance of accurately modelling the geoid has increased in recent years with the usage of satellite positioning systems such as the Global Positioning System (GPS), GALILEO and GLONASS. GPS provides height information relative to a best-fitting earth ellipsoid rather than the geoid [1]. The relationship between the geoid and the ellipsoid must be known to convert ellipsoidal heights derived from GPS to conventional (and more meaningful) orthometricheights[2]. The situation is illustrated in Fig. 1.

The relation between ellipsoid, geoid and geoid height can be written following simple equation

$$H = h - N \qquad (1)$$

where h are ellipsoidal heights obtained from GPS observations, H are orthometric heights derived for example from spirit levelling and gravimetry, N are geoid heights [3],[4],[5].

Geoid determination methods can be classified according to the available data and the methods used. These methods are: Astro-geodetic, gravimetric, Global geopotential, remove restore [6] and GPS/levelling. The GPS/levelling method is now preferred because of the increase of GPS measurements and its simple equations. The GPS/levelling geoid height determination method can be used for regional or local geoid determinations. The geoid heights determined by the GPS/levelling method can be also used as data in geoid height determinations by polynomial coefficients, fuzzy logic, artificial neural network and finite element method.

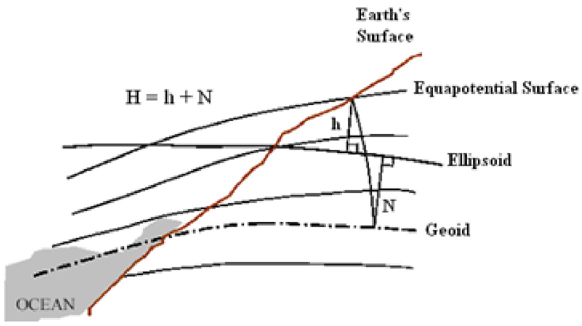

Fig. 1: The geometrical relationship between orthometric and ellipsoidal height and geoid height [7].

II. ADAPTIVE NETWORK BASED FUZZY INFERENCE SYSTEMS

Adaptive Network based Fuzzy Inference Systems (ANFIS) are feed-forward adaptive networks which are functionally equivalent to fuzzy inference systems. The basic idea of ANFIS

can be described as follows: A fuzzy inference system is typically designed by defining linguistic input and output variables as well as an inference rule base. However, the resulting system is just an initial guess for an adequate model. Hence, its premise and consequent parameters have to be tuned based on the given data in order to optimise the system performance. In ANFIS this step is based on a supervised learning algorithm [8].For simplicity, assume that the fuzzy inference system under consideration has two inputs x and y and one output f. Additionally, suppose that the rule base contains two fuzzy if-then rules of the Takagi and Sugeno's type [9], [10], [11], [12], [13] as

Rule 1: If X is A1 and Y is B1; then f1= p1x + q1y + r1.

Rule 2: If X is A2 and Y is B2; then f2 = p2x + q2y + r2.

(In the Same way, fuzzy inference system under consideration has three inputs x, y and z and one output f. two fuzzy if-then rules of the Takagi and Sugeno's type as

Rule 1: If X is A1 and Y is B1 and Z is C1; then f1= p1x + q1y +s1z + r1.

Rule 2: If X is A2 and Y is B2 and Z is C2; then f2 = p2x + q2y +s2z + r2)

The associated ANFIS architecture is illustrated in Fig. 2 [14]. The functions of each layer can be summarised such that In layer 1, inputs were divided subspaces using selected membership function. The membership can be chosen to be a Gaussian shaped with the maximum value equal to 1 and minimum value equal to 0 such as, e.g., the Gaussian function (shown in Fig. 3)[15].

Where, $\{\sigma, c_i\}$ is the premise parameter set. In layer 2, firing strength of a rule is calculated by multiplying incoming signals. In layer 3, firing strengths are normalised and in layer 4, consequent parameters $\{p_i, q_i, r_i\}$ are determined and in layer 5, final output is obtained by summing of all incoming signals. The training algorithm, namely ANFIS, was developed by Jang [1993]. Basically, ANFIS takes the initial fuzzy model and tunes it by means of a hybrid technique combining gradient descent back-propagation and mean least-squares optimization algorithms (see Fig. 4). At each epoch, an error measure, usually defined as the sum of the squared difference between actual and desired output, is reduced. Training stops when either the predefined epoch number or error rate is obtained. The gradient descent algorithm is mainly implemented to tune the non-linear premise parameters while the basic function of the mean least-squares is to optimize or adjust the linear consequent parameters. [7], [8], [16], [17], [18], [19], [20], [21], [22], [23], [24].

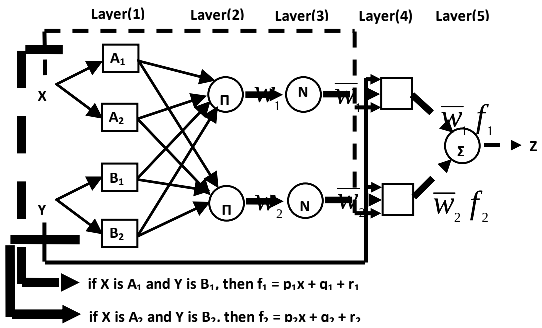

Fig. 2. A simple two inputs, two rules and a single output of ANFIS structure **[14]**

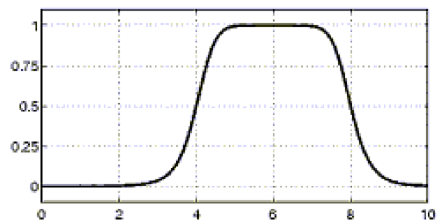

Fig. 3: Physical meanings of the parameters in the Gaussian membership function [15].

Fig. 5 shows an example of fuzzy partitioning of the input space in case of two inputs. Each input is divided by three subsets. So, the input space is partitioned into nine fuzzy subspaces, leading to nine fuzzy if-then rules in the ANFIS.

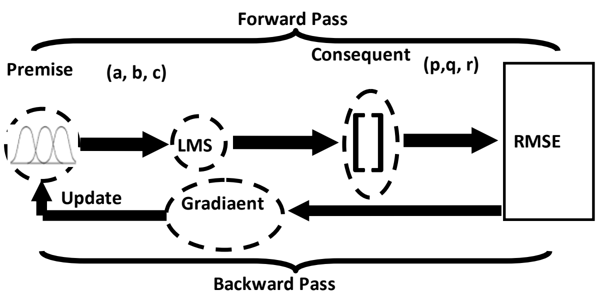

Fig. 4: ANFIS learning using hybrid technique (LMS :Least mean square, RMSE :root mean square error) [25]

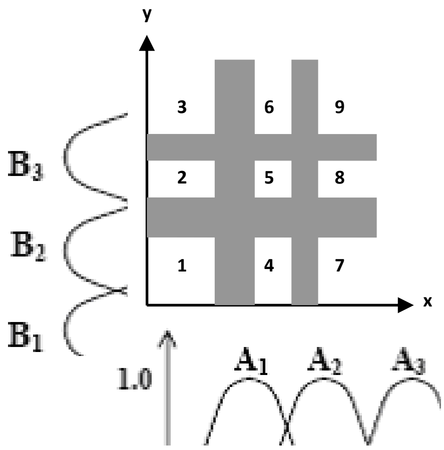

Fig. 5: Corresponding fuzzy subspaces for a two-input Type-3 ANFIS with 9 rules [7],[8],[26].

III. CONSEQUENT PARAMETERS ESTIMATION

According to the proposed simple ANFIS architecture (shown in Fig. 2), it can be observed that given the values of the premise parameters, the overall output can be expressed as a linear combination of the consequent parameters. More explicitly, the output *Z* in Fig.2 can be rewritten as:

$$\begin{aligned} Z &= \overline{w}_1 f_1 + \overline{w}_2 f_2 \\ &= (\overline{w}_1 x) p_1 + (\overline{w}_1 y) q_1 + (\overline{w}_1) r_1 + (\overline{w}_2 x) p_2 \end{aligned} \quad (2)$$

By fixing the elements included in the normalized firing strength of the rules and the above expression in Equation 2 is linear in the consequent parameters (p_1, q_1, r_1, p_2, q_2, and r_2) [13]. Therefore, the matrix form of Equation 2 can be written as:

AX = B (3)

Where X is an unknown vector whose elements are the linear consequent parameters of all rules. Given that the number of these linear consequent parameters is (M) and the number of training input output data pairs is (N), then the dimensions of X, A and B are N×M, M×1 and N×1, respectively. Since N is always greater than M, the system of equations in (3) is over-determined and generally there is no exact or unique solution that can be attained. Instead, a least-squares estimate (LSE) of X is sought to minimize the squared error . $\|\mathbf{AX} - \mathbf{B}\|^2$ This is a standard problem that forms the base in many applications like linear regression, adaptive filtering and signal processing. The most well known formula for solving such over-determined system of equations uses the pseudo-inverse of X:

$X^* = (A^TA)^{-1}A^TB$ (4)

Where AT is the transpose of A and $(A^TA)^{-1}A^T$ is the pseudo inverse of A if (A^TA) is non-singular [7], [20], [24], [25], [27], [28], [29], [30], [31].

IV. DATA

In this study three different data sets were used to determine the best suitable subset numbers. These 254, 504 and 1006 points whose latitude, longitude, ellipsoidal height and orthometric height are known were used to construct Fuzzy models in the region. The points are homogenously distributed and randomly selected in Istanbul; the point density is nearly one point in 20, 10 and 5 km2 respectively. The data covers the region between 41° 30´2.78” >φ> 40° 48´13”.75 and 29° 54´ 24”.24 >λ> 27° 59´ 3”.05. The standard deviation of the ellipsoidal heights after the adjustment of the network has been found to be ± 2.56 cm [32]. To check for the calculation, randomly selected 173 points which had not been included in the preparation of the Fuzzy models were used.

V. RESULTS

In this study, two different fuzzy models were constructed. First group fuzzy model is constructed with two inputs (latitude and longitude taken as inputs) and one output (geoid height as taken output) and the second group fuzzy model is formed by three inputs (latitude, longitude and ellipsoidal heights taken as inputs) and one output (geoid height as taken output). Inputs were divided into different subsets which give the best results in both fuzzy models. Therefore, inputs are divided into 9, 9 and 14 different subsets in two inputs and one output fuzzy model using 254, 504 and 1006 points respectively. Likewise, inputs are divided into 4, 4 and 5 different subsets in three inputs and one output fuzzy model using 254, 504 and 1006 points respectively.

The efficiency of the ANFIS approximation was compared to the results obtained by the GPS/levelling method. The performance of the ANFIS approximation was tested at the model points and at the 173 test points. The differences between geoid heights obtained by the GPS/levelling method and the Fuzzy model results, number of lineer and non-lineer parameters are summarised in Table 1, Table 2 and Table 3.

It can be seen that the RMSE (which is calculated with $\sqrt{\sum vv/n}$ where v = error and n = number of points) values vary from ± 2.21 cm to ± 5.45 cm and from

Table 1: Summary of the resulsts obtained by 254 points

Number of subsets	Number of lineer parameters	Number of non- lineer parameters	Total parameters	Number of rules	MSE at Model Points	MSE at TestPoints
2x2	12	8	20	4	5.45	6.33
3x3	27	12	39	9	4.47	5.84
4x4	48	16	64	16	4.04	5.32
5x5	**75**	**20**	**95**	**25**	**3.59**	**4.58**
6x6	108	24	132	36	3.18	4.67
7x7	143	28	171	49	2.96	5.92
8x8	192	32	224	64	2.74	7.63
9x9	243	36	279	81	2.60	16.61
10x10	300	40	340	100	2.21	53.22
2x2x2	32	12	44	8	3.80	5.56
3x3x3	108	18	126	27	2.71	4.93
4x4x4	256	24	280	64	1.64	12.18
5x5x5	500	30	530	125	1.09	222.33

Table 2: Summary of the resulsts obtained by 254 points

Number of subsets	Number of lineer parameters	Number of non- lineer parameters	Total parameters	Number of rules	MSE at Model Points	MSE at TestPoints
2x2	12	8	20	4	5.37	5.99
3x3	27	12	39	9	4.43	4.97
4x4	48	16	64	16	4.04	4.87
5x5	75	20	95	25	3.72	4.70
6x6	108	24	132	36	3.36	4.25
7x7	143	28	171	49	3.14	4.07
8x8	192	32	224	64	2.91	3.85
9x9	**243**	**36**	**279**	**81**	**2.82**	**3.51**
10x10	300	40	340	100	2.42	4.68
2x2x2	32	12	44	8	3.93	4.79
3x3x3	108	18	126	27	3.09	4.51
4x4x4	**256**	**24**	**280**	**64**	**2.46**	**3.88**
5x5x5	500	30	530	125	1.90	5.56

Table 3: Summary of the results obtained by 254 points

Number of subsets	Number of lineer parameters	Number of non- lineer parameters	Total parameters	Number of rules	MSE at Model Points	MSE at TestPoints
2x2	12	8	20	4	4.84	6.38
3x3	27	12	39	9	4.39	5.96
4x4	48	16	64	16	4.10	5.62
5x5	75	20	95	25	3.62	5.15
6x6	108	24	132	36	3.49	4.87
7x7	143	28	171	49	3.08	4.58
8x8	192	32	224	64	3.03	4.32
9x9	243	36	279	81	3.00	4.11
10x10	300	40	340	100	2.73	3.85
11x11	363	44	407	121	2.61	3.61

12x12	432	48	480	144	2.29	3.22
13x13	**507**	**52**	**559**	**169**	**2.33**	**2.93**
14x14	588	76	664	196	2.17	3.10
15x15	675	100	775	225	2.07	3.86
2x2x2	32	12	44	8	3.95	5.12
3x3x3	108	18	126	27	3.04	4.46
4x4x4	256	24	280	64	2.54	4.03
5x5x5	**500**	**30**	**530**	**125**	**2.22**	**3.67**
6x6x6	864	36	900	216	2.15	5.28

± 4.58 cm to ± 53.22 cm for model and test points using 254 points by two inputs and one output fuzzy models, respectively. On the other hand, numbers of total parameter vary from 20 to 279 in the models. Subsets divided by 5x5 can be used as the best fuzzy model in this group. RMSE values vary from ± 1.09 cm to ± 3.80 cm and from ± 4.93 cm to ± 222.33 cm for model and test points using 254 points by three inputs and one output fuzzy models, respectively. On the other hand, numbers of total parameter vary from 44 to 530 in the models. Subsets divided by 3x3x3 can be used as the best fuzzy model in this group

RMSE values also vary from ± 2.42 cm to ± 5.37 cm and from ± 3.51 cm to ± 5.99 cm for model and test points using 504 points by two inputs and one output fuzzy models, respectively. On the other hand, numbers of total parameter again vary from 20 to 279 in the models. Subsets divided by 9x9 can be used as the best fuzzy model in this group RMSE values vary from ± 1.90 cm to ± 3.93 cm and from ± 3.88 cm to ± 5.56 cm for model and test points using 504 points by three inputs and one output fuzzy models, respectively. On the other hand, numbers of total parameter also vary from 44 to 530 in the models. Subsets divided by 4x4x4 can be used as the best fuzzy model in this group

RMSE values also vary from ± 2.07 cm to ± 4.84 cm and from ± 2.93cm to ± 6.38 cm for model and test points using 1006 points by two inputs and one output fuzzy models, respectively. On the other hand, numbers of total parameter again vary from 20 to 775 in the models. Subsets divided by 13x13 can be used as the best fuzzy model in this group RMSE values vary from ± 2.15 cm to ± 3.95 cm and from ± 3.67 cm to ± 5.28 cm for model and test points using 1006 points by three inputs and one output fuzzy models, respectively. On the other hand, numbers of total parameter also vary from 44 to 900 in the models. Subsets divided by 5x5x5 can be used as the best fuzzy model in this group

According to this study, the best fuzzy models can be constructed with total number of parameters is nearly half of the number of points used in fuzzy models. For example, a two inputs and one output fuzzy model can be formed by dividing five subsets of each inputs using 254 points. Number of lineer parameters is 75 and number of non-lineer parameters is 20 and total number of parameters is 95. This is nearly half of the total number of points to contruct fuzzy model. A two inputs and one output fuzzy model also can be formed by dividing thirteen subsets of each inputs using 1006 points. Number of lineer parameters is 507 and number of non-lineer parameters is 52 and total number of parameters is 559. This is again nearly half of the total number of points to contruct fuzzy model.

In the same way, a there inputs and one output fuzzy model can be constructed by dividing four subsets of each inputs using 504 points. In this case, Number of lineer parameters is 256 and number of non-lineer parameters is 24 and total number of parameters is 280. This is also nearly half of the total number of points to contruct fuzzy model.

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VI. CONCLUSION

Adaptive Network based Fuzzy Inference Systems (ANFIS) can be used as a computation tool for many areas such as geodetic sciences, civil engineering, mechanical engineering, electrical

engineering and many other areas. Determination of number of subsets is critical in ANFIS because it cannot be determined easily. This is normally a trial and error job. However, if how many subsets can be selected known approximately, computation time is reduced dramatically.

According to this study, the best fuzzy models can be constructed with total number of parameters is nearly half of the number of points used in fuzzy models. To construct a two inputs and one output fuzzy model using 254 points, inputs can be divided five subsets to get best results. In the same way, to form a two inputs and one output fuzzy model using 1006 points, inputs can be divided thirteen subsets to get best results. Again, dividing five subsets gives the best results a three inputs and one output fuzzy model using 1006 points.

Another factor effects result of ANFIS is type of membership function. Studies show that Gauss and Gauss2 membership functions give the best results.

While using ANFIS, one has to care about some aspects for example, the number of parameters (both premise and consequent) in ANFIS has to be less than the number of training data pairs. This is to avoid the over fitting phenomenon, which does not allow a generalisation of the established fuzzy inference system.

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